Final Project Report

An application of Monte Carlo Simulation in Portfolio Optimization

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Table of contents

Introduction

Portfolio optimization is a significant and hotable topic in the field of financial math due to its huge application for any investors. Monte Carlo Simulation, which is a statistical technique applied in finance, will give us a tool that allows us to obtain a distribution of results for any statistical problem with multiple inputs sampled over and over again.

Research question

This project discusses implementation of Monte Carlo Simulations for portfolio optimization and asset allocation. To be more specific, this technique aims to construct many random portfolios of equities in order to find three specific popular portfolio types: minimum risk, maximum return, and maximum Sharpe Ratio.

Literature review

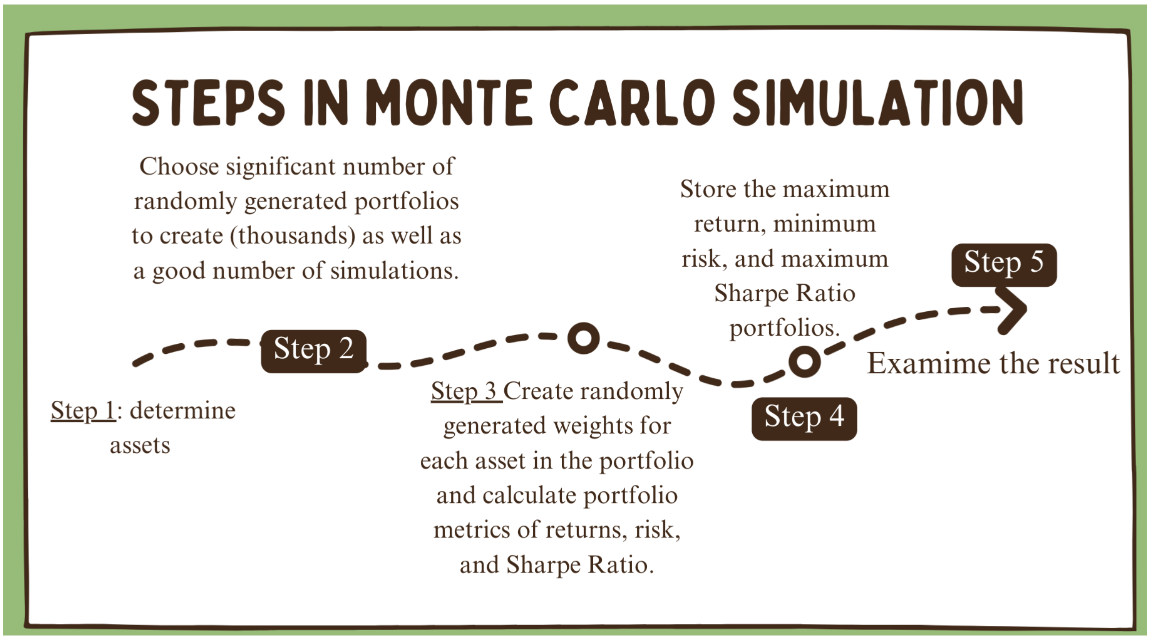
Monte Carlo simulation is a powerful computational technique for portfolio analysis. By running thousands of simulations, they were able to generate a distribution of portfolio returns and evaluate risk measures such as Value at Risk (VaR) and identify optimal portfolios with higher expected returns and lower risks.

Compared with Markowitz's idea, which relies on assumptions of normally distributed returns and stationery market conditions, Monte Carlo simulation allows for the incorporation of more realistic and complex distributions of asset returns, capturing non-normalities and dynamic market behavior. Moreover, Monte Carlo simulation can be combined with other optimization techniques, such as maximizing the Sharpe ratio, to identify portfolios that offer an optimal balance between risk and return.

Methodology

Monte Carlo simulation

Monte Carlo simulation is a computational technique that utilizes random sampling and statistical analysis to model and evaluate complex systems or processes. By generating numerous iterations of possible outcomes, it provides insights into the range of potential results and helps make informed decisions under uncertainty.



Computational techniques

To perform the simulation, I used some library in Python to work with the data or data simulations, such as pandas or numpy. In terms of visualization, some visualization libraries such as seaborn and matplotlib have been used. Yfinance library is utilized to scrap the data from the existing data library.

A details guide using Python programming language

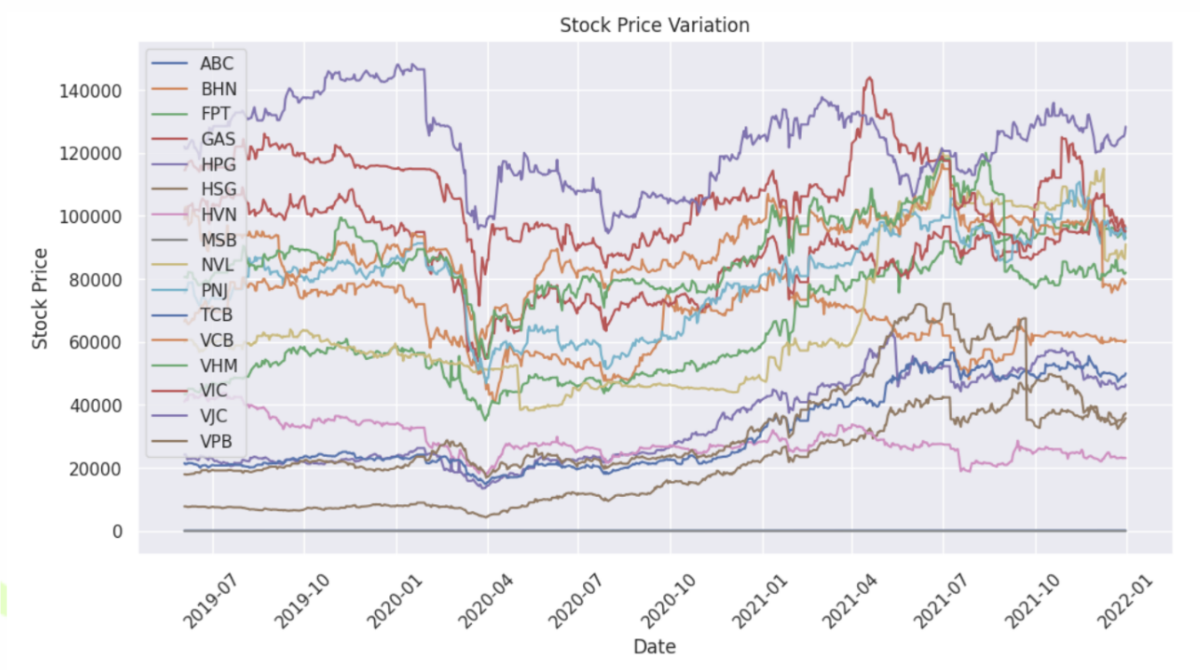
By following this instruction, the reader can create another portfolio simulation output based on the existing code.

(1) Access to the ipynb file (or html file just to watch, not perform any programming) consists of the Python code to generate simulations based on past stocks data. Then, we install the needed library in the part library installation.

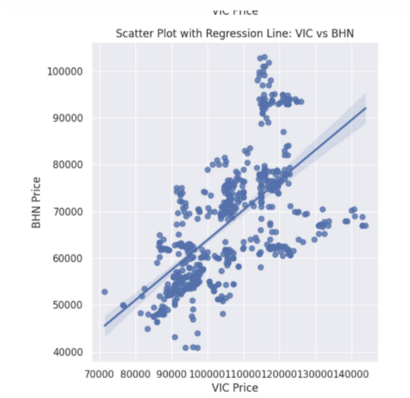
(1) Gather the needed stock by filling the stock name and time (start and end).
(2) Perform past data description using some tools such as line graph, boxplot, or scatter plot to see some notable characteristic of the stocks. This part is optional.
(3) Prepare for the simulations by calculating the annual returns and covariance matrix, enter the number of simulations/portfolios/weights
(4) Now we do the simulations in two loops (the explanation of the code can be found in the file)
(5) The simulation returns the result in sim_port. Now we can do analysis and make decisions by visualizing the simulations using seaborn (to draw distributions) or scatter plot (to compare the advantages and disadvantages and decide your desired outcome).

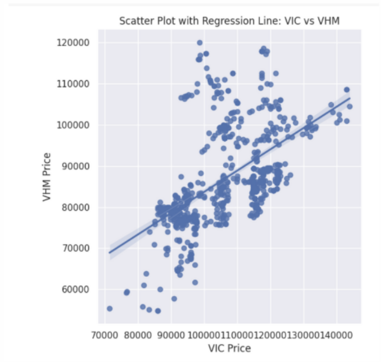
Data description

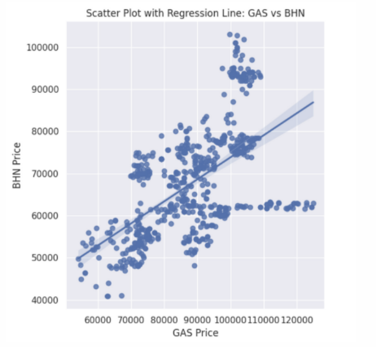
In this project, I collect data from 16 Vietnamese random types of stock prices chosen from Yahoo finance from 1st June 2019 to 1-1-2022 (in about 2.5 years), namely "VIC","VHM","GAS","VCB","HPG","TCB","FPT", "HVN", "VJC", "BHN", "MSB", "VPB", "HSG", "PNJ","NVL", "ABC"].



Looking at the price variation, we can see some similar trends at the same time between some stocks. To verify these predictions, I also drew some scatter plots between pairs of stock data. Here are some pairs of stock types that exhibit a higher correlation with each other.







The stock price distribution also provides us an overview of the price information. For example, in the output data, if we are looking for stock with low price, we can consider the portfolio with a small amount of HSG or HPG.

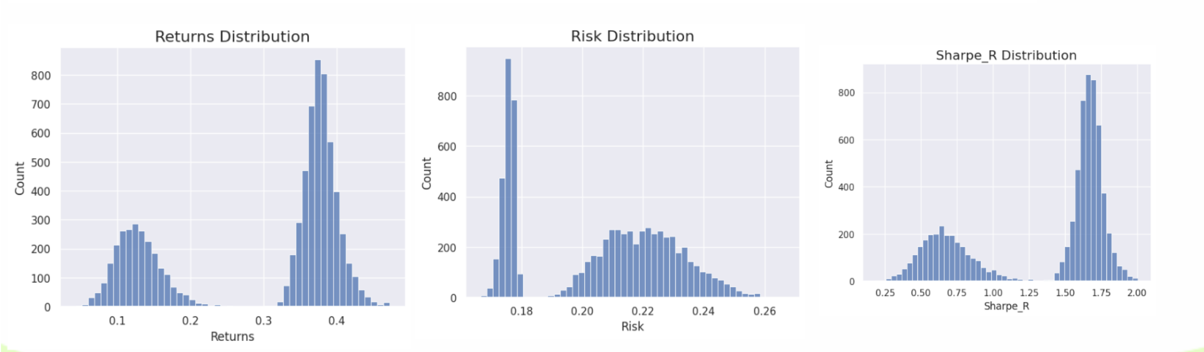
With this past stock data, 5,000 random portfolios are generated in each of the 2,500 simulations that are made. After each simulation, we take three portfolio types (Max return, Min risk, Max Sharpe R) to exhibit some common investor goals, which provides a good example for the implementation of this method. Finally, we have 7500 (by taking 3 in each of 2500 simulations) portfolios generated in the final output (*sim_port*: simulation portfolios), which are in this form (see clearer in ipynb file). Overall, this file contains 7500 rows of portfolios, each row includes information of portfolio return, risk, Sharp ratio, and the weight of each asset (in this case is stock).

```
sim_port.head()
```

	Returns	Risk	Sharpe_R	ABC_Weight	BHN_Weight	FPT_Weight	GAS_Weight	HPG_Weight	HSG_Weight	HVN_Weight	MSB_Weight	NVL_Weight	PNJ_Weight	TCB_Weight	VCB_Weight	VHM_Weight	VIC_Weight	VJC_Weight
0	0.365814	0.225132	1.580468	0.093372	0.022754	0.059740	0.006515	0.093522	0.134163	0.030483	0.020265	0.062009	0.005522	0.131195	0.116357	0.012737	0.016654	0.060528
1	0.103459	0.174695	0.534985	0.136938	0.086959	0.001910	0.011427	0.039617	0.024649	0.043452	0.026297	0.104335	0.093525	0.003574	0.046308	0.106890	0.119838	0.123101
2	0.336064	0.201228	1.620371	0.133931	0.016020	0.067570	0.022558	0.066328	0.120373	0.032643	0.091134	0.122356	0.016649	0.135402	0.085435	0.059994	0.021122	0.001429
3	0.396632	0.242769	1.592590	0.041186	0.040280	0.019888	0.133463	0.020414	0.229216	0.065418	0.014133	0.016613	0.030568	0.107021	0.006660	0.003994	0.019806	0.124365
4	0.138856	0.176022	0.732047	0.142632	0.031897	0.059638	0.020878	0.021636	0.020080	0.031536	0.037418	0.090117	0.106343	0.073357	0.021203	0.071045	0.125137	0.133844

Results and discussion

7500 portfolio simulations



The distributions show where portfolios containing these equity securities along with the used criteria can be found in terms of risk, return, and Sharpe ratio.

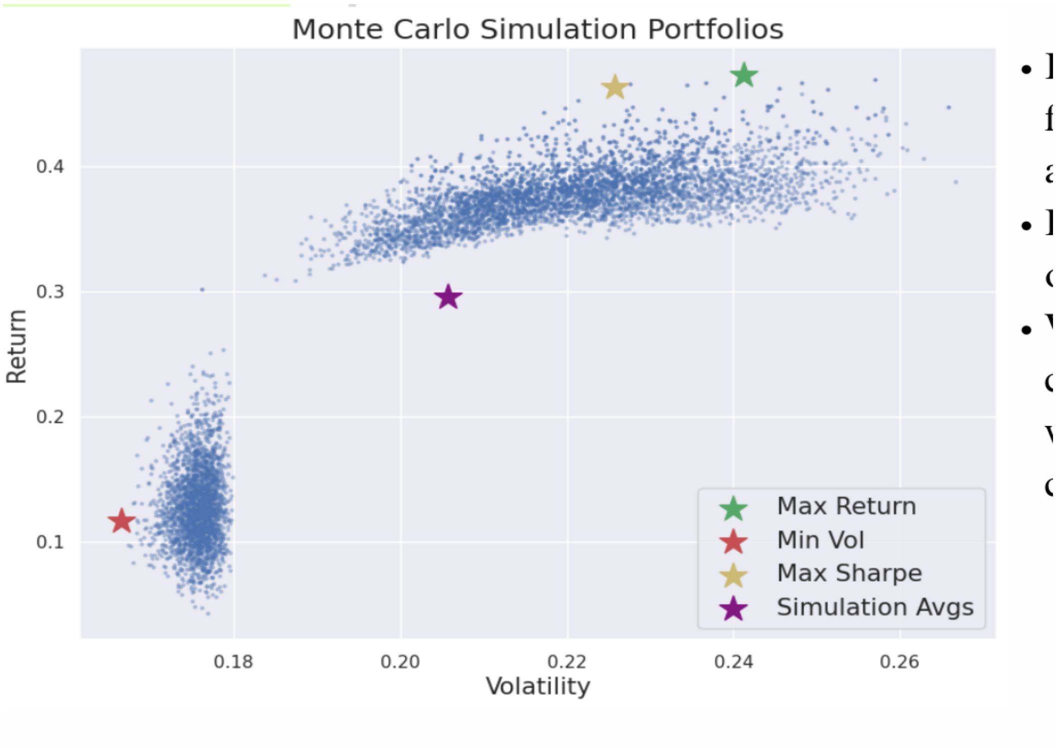
For returns, it can be seen most are around more than 30% in annual returns, so any portfolio that can have something greater than that such as the ones at 45% are better than most. Inversely, those with portfolios to the left under 30% can be understood to be underperforming with the given conditions and assets.

The same idea can be understood from the risks generated. As seen, most had a volatility right-left of 18% with quite a few being around 22%. The portfolios with risks above 20% and 26% can be seen as underperforming in regard to controlling risk under these conditions if that is an important aspect for the investor. Volatilities of 18% are the lowest and can be considered the highest if one is seeking smaller risk under these conditions.

Finally, the most extreme portfolios can be found from all the simulations and randomly generated portfolios. This gives the highest return one, the smallest risk one, and the highest Sharpe ratio one.

It is suggested to use the average portfolio based on return and risk using these metrics. Additionally, we can represent all portfolios on an efficient frontier scatter plot, which visually displays their positions and metrics relative to each other.

This graph exhibits how Monte Carlo simulations can find an optimal portfolio, **covering essentially all possible scenarios.**



For investors seeking to maximize returns, the green star portfolio stands out as a favorable choice on the scatter plot. It represents a portfolio with an optimal balance between risk and return, offering potentially higher returns compared to other portfolios.

On the other hand, investors prioritizing risk minimization above all else can opt for the red star portfolio. Positioned on the scatter plot, it represents a portfolio with the lowest level of risk compared to the other portfolios evaluated.

The scatter plot thus provides a visual representation of the trade-off between risk and return, allowing investors to make informed decisions based on their specific investment objectives.

As an example, it is clear how the maximum Sharpe ratio portfolio (yellow star) is a better choice than the average metrics portfolio (purple star) since it has a much higher return while still having a smaller amount of risk. That's why the Sharpe ratio is a widely used metric that compares portfolio returns to the risk-free rate and overall portfolio risk. By using a basic filter in the output dataset, we can choose our desired portfolio with wanted properties based on the analysis.

Challenges and further application

Challenges

When using Monte Carlo simulations in portfolio analysis, several factors should be considered.

(1) Computational complexity is a challenge as running numerous iterations and simulations can require significant computational resources and time.
(2) Data quality and availability are crucial, as accurate and reliable data on asset returns and correlations are needed for meaningful results.
(3) Assumption and model selection pose challenges as well, as choosing appropriate assumptions and models that reflect real-world dynamics is vital.
(4) Finally, interpreting simulation results and making informed decisions based on them can be challenging, requiring careful analysis and understanding of the limitations of the simulation approach.

Further application

There are additional metrics that can be utilized alongside different methods. To improve accuracy and usefulness, more simulations and random portfolios can be generated. This approach can be extended to other methods like Performance Evaluation and Scenario Analysis, Value at Risk (VaR) Estimation, and portfolio diversification.

Conclusion

These three approaches demonstrate how Monte Carlo simulations can be used to improve portfolio allocation. However, there are challenges involved in this application.

As technology progresses, it remains an effective tool, but accurate assumptions and data are necessary. Additionally, the computational complexity can be demanding, as it requires generating numerous random scenarios and simulating portfolio performance for each one. Despite these challenges, Monte Carlo simulations offer valuable insights for investors and financial analysts.

Acknowledgement

Last but not least, I am personally thankful for the support of Dr. Le Nhat Tan through the course which motivates me to explore this interesting problem. Any incompatible content can be more understandable by running the code, reading the explanation again or exploring some similar resources. And I apologize for any misunderstanding due to my knowledge.

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